REMARKS

The comments of the applicant below are each preceded by related comments of the examiner (in small, bold type).

> **Claim 6 is objected to because of the following informalities:**
> **Claim 6, Line 7-8: Appears to be missing step (b).**
> **Appropriate correction is required.**

Claim 6 has been amended.

> **Claims 1-28 are rejected under 35 U.S.C. 102(b) as being anticipated by Lazarus et al. (U.S. Patent Number: 6,430,539).**

Regarding independent claim 1, instead of applying a selected model development process to a first subset of historical data to generate a "tentative predictive model" and applying the validated model development process to a full set of historical data ... to generate a "final predictive model", Lazarus generated only one predictive model for each merchant segment based on transaction data (column 11, lines 8-10).

Lazarus clustered merchants into segments based on actual spending patterns to predict future spending of an individual consumer in a specific merchant group (column 2, lines 23-30, column 8, lines 61-63, column 10, line 61-column 11, line 2). For each merchant segment, transaction data related to multiple consumers (accounts 1...N) was used to generate a predictive model (FIG. 9 and column 31, lines 13-24). In particular, to build a predictive model for one merchant segment, Lazarus trained a neural network (column 31, lines 30-32). During the training, Lazarus used five selected sets of input data 802a-802d and target data 803a-803d from 16 months of transaction data (FIG. 8 and column 28, line 59-column 29, line 5). The predictive model for a merchant segment was generated after the training. Lazarus evaluated the performance of the trained/generated predictive model using another data set 804 selected from the 16 months of transaction data (column 29, lines 7-13). Finally, a set of data 806 that extended from a selected date (end of Feb.) back the length of each input data set 802a-802d was input into the predictive model to predict behavior of the consumers from the selected date (March to end of May, column 29, lines 14-25).

In addition, as explained previously, instead of "selecting a process for developing a predictive model for the system from among multiple possible model development processes," as recited by claim 1, Lazarus used one approach, a neural network with a conventional multi-layer organization and backpropagation training (column 31, lines 30-32). Lazarus also did not describe and would not have made obvious "if the selected model development process is so validated, then applying the validated model development process to a full set of historical data that includes the first and second subsets to generate a final predictive model," as recited by claim 1. None of Lazarus' data sets 802a-802d, alone or in combination, was a full set of the 16 months of transaction data. Data sets 804 and 806 were not historical data used for generating a predictive model and neither set was a full set of the 16 months of transaction data either. One skilled in the art would not have used the full set of 16 months of data in generating a predictive model, at least because Lazarus required that the prediction window for the performance evaluation of the predictive model did not overlap any of the prediction windows of the training data sets (column 29, lines 7-10). The applicant withdraws the applicant's discussion of Lazarus' use of a full set of historical data contained in the reply filed on January 11, 2010. Lazarus stated:

> Accordingly, what is needed is the ability to model consumer financial behavior based on actual historical spending patterns that reflect the time-related nature of each consumer's purchase. Further, it is desirable to extract meaningful classifications of merchants based on the actual spending patterns, and from the combination of these, predict future spending of an individual consumer in specific, meaningful merchant groupings. (column 2, lines 23-30)

> The merchant vectors are then clustered 304 into merchant segments. The merchant segments generally describe groups of merchants which are naturally (in the data) shopped at "together" based on the transactions of the many consumers. (column 10, line 65-column 11, line 2)

> With the merchant segments now defined, a predictive model of spending behavior is created 306 for each merchant segment. The predictive model for each segment is derived from observations of consumer transactions in two time periods: an input time window and a subsequent prediction time window. Data from transactions in the input time window for each consumer (including both segment specific and cross-segment) is used to extract independent variables, and actual spending in the prediction window provides the dependent variable. (column 11, lines 8-17, emphasis added)

> The training observations for each segment are input into the segment predictive model generation module 530 to generate a predictive model for the segment. FIG. 9 illustrates the overall logic of the predictive model generation process. The master files 408 are organized by accounts, based on account identifiers, here illustratively, accounts 1 through N. There are M

segments, indicated by segments 1 through M. The DPPM generates for each combination of account and merchant segment, a set of input and blind observations. The respective observations for each merchant segment M from the many accounts 1 . . . N are input into the respective segment predictive model M during training. Once trained, each segment predictive model is tested with the corresponding blind observations. Testing may be done by comparing for each segment a lift chart generated by the training observations with the lift chart generated from blind observations. Lift charts are further explained below. (column 31, lines 13-29, emphasis added)

The predictive model generation module 530 is preferably a neural network, using a conventional multi-layer organization, and backpropagation training. (column 31, lines 30-32, emphasis added)

More particularly, the input for the observation generation module 530 are the master files 408. The output is a set of observations for each account. Each account receives three types of observations. FIG. 8 illustrates the observation types. (column 28, lines 48-52, emphasis added)

The first type of observations are training observations which are used to train the predictive models that predicts future spending within particular merchant segments. (column 28, lines 53-55)

In FIG. 8, there are shown a 16 months of transaction data, from March of one year, to June of the next. Training observations are selected prior to the date of interest, November 1. The input window includes the 4 months of past data to predict the next 2 months in the prediction window. The first input window 802a thus uses a selected date of July 1, includes March-June to encompass the past transactions; transactions in July-August form the prediction window 803a. The next input window 802b, uses August 1 as the selected date, with transactions in April-July as the past transactions, August-September as prediction window 803b. The last input window for this set is 802d, which uses November 1 as its selected date, with an prediction window 803d of observations in November-December. (column 28, line 59-column 29, line 6, emphasis added)

The second type of observations are blind observations. Blind observations are observations where the prediction window does not overlap any of the time frames for the prediction windows in the training observations. Blind observations are used to evaluate segment model performance. In FIG. 8, the blind observations 804 include those from September to February, as illustrated. (column 29, lines 7-13, emphasis added)

The third observation type is action observations, which are used in a production phase. Action observations have only inputs (past transactions given a selected date) and no target transactions after the selected date. These are preferably constructed with an input window that spans the final months of available data. These transactions are the ones on which the actual predictions are to be made. Thus, they should be the transactions in an input window that extends from a recent selected date (e.g most recent end of month), back the length of the input window used during training. In FIG. 8, the action observations 806 span November 1 to end of February, with the period of actual prediction being from March to end of May. (column 29, lines 14-25, emphasis added)

In the production phase, the system is used to predict spending, either in future time periods for which there is no actual data as of yet, or in a recent past time period for which data is available and which is used for retrospective analysis. (column 11, lines 24-27, emphasis added)

The examiner stated (emphasis added):

> **selecting a process for developing a predictive model for the system from among multiple possible model development processes (<u>e.g., highest correlation with the segment vector, highest average transaction amount, or other selective criteria</u>) (see Table 13; and Col. 37, Lines 54-65);**

Table 13 and the description in column 37, lines 54-65 had nothing to do with developing a predictive model, let alone "selecting a process for developing a predictive model for the system from among multiple possible model development processes." This part of Lazarus described targeting populations for each merchant segment to send predetermined promotional offers to the targeted population. (column 37, lines 40-43)

The examiner also stated (emphasis added):

> **applying the selected model development process to the first subset of historical data to generate <u>the tentative predictive model (e.g., segment models)</u> (see Table 13 and Col. 38, Lines 23-38);**
>
> **selecting a second subset of the historical data (e.g., certain merchants in a segment; and Figure 9 for segment 1, segment 2, ... segment M) (see Col. 37, Lines 54-65), the second subset (e.g., each segment) being less than all of the historical data and being at least a portion of a complementary dataset of the first subset (e.g., overlapped segments) or being randomly selected from the historical data and independent of the first subset (see Col. 38, Lines 24-53);**
>
> **applying the tentative predictive model (e.g., segment models) to the selected second subset (e.g., overlapped segments) (see Col. 38, Lines 24-53), determining whether results of applying the tentative predictive model to the selected second subset validate that the selected model development process will produce a final predictive model that is accurate for data that is not part of the historical data (e.g., generate lift charts for the targeting population in the segment, and for overlapped combined segments) (see Col. 38, Lines 24-53), if the selected model development process is so validated (e.g., lift chart useful for validating the performance of the predictive models) (see Col. 34, Lines 20-23), then <u>applying the validated model development process to a full set of historical data that includes the first and second subsets generate a final predictive model (e.g. segment models may be merged to produce a single lift chart)</u> (see Col. 38, Lines 37-39), and using the final predictive model (e.g., target promotional offers) (see Figure 3).**

The examiner interpreted Lazarus' model for each merchant segment as a "tentative predictive model" and Lazarus statement "[W]ithin each offer (e.g. offer ID 1) the segment models may be merged to produce a single lift chart ...." (column 38, lines 36-40) as describing "applying the validated model development process to a full set of historical data that includes the first and second subsets to generate a final predictive model." The applicant disagrees.

By stating "segment models may be merged", Lazarus did not apply "<u>the validated model development process</u> [that generated the tentative predictive model] ... to generate a final predictive model." Lazarus merged segment models <u>to produce a single lift chart</u>. It is unclear

whether a merged model was produced and if so, how such a merged model was generated. The mere statement of "segment models may be merged ..." did not describe and would not have made obvious a final predictive model that is generated by "applying the validated model development process [that generated the tentative model]...."

Even if there were a merged model for a promotion offer, only selected models for selected merchant segments were used for the merge and the merged model would not have been based on "a full set of historical data" because there are at least other unselected merchant segments including other transaction data not used in the selected merchant segments. As explained previously, each model for the merchant segments did not use a full set of transaction data. Even if all models for all merchant segments were combined, the merged model would not have been based on "a full set of historical data".

> **As to independent claim 6, Lazarus discloses a machine-based method comprising:**
>
> **in connection with a project (e.g., predictive modeling of consumer financial behavior) (see Abstract), selecting a model development process from multiple model development processes to apply on a first subset of less than all of a set of historical data to generate a first tentative predictive model (e.g., highest correlation with the segment vector, highest average transaction amount, or other selective criteria) (see Table 13; and Col. 37, Lines 54-65), applying the selected model development process including**
>
> **a) automatically transforming variables of the subset of the historical data (e.g., variables) (see Col. 11, Lines 13-23),**
>
> **automatically generating the first tentative predictive model (e.g., segment models) (see Table 13 and Col. 38, Lines 23-38), and**
>
> **c) automatically generating performance measures of the first tentative predictive model (e.g., confirm model performance) (see Col. 4, Lines 25-26),**
>
> **determining a validity of the selected development process based on the performance measures of the first predictive model (e.g., validation and analysis of the segment predictive models done to confirm model performance) (see Col. 11, Lines 21 -23);**
>
> **applying the validated model development process (e.g., lift chart useful for validating the performance of the predictive models) (see Col. 34, Lines 20-23; and Col. 38, Lines 23-38) to a full set of historical data (e.g., based on historical data) (see Col. 4, Lines 11-16) that includes the subset (e.g., certain merchants in a segment; and Figure 9 for segment I, segment 2, ... segment M) (see Col. 37, Lines 54-65) to generate a second (e.g., overlapped segments) (see Col. 38, Lines 24-53), final model (e.g. segment models may be merged to produce a single lift chart) (see Col. 38, Lines 37-39), and using the final predictive model (e.g., target promotional offers) (see Figure 3).**

Independent claim 6 is patentable for at least reasons similar to those discussed for independent claim 1.

All of the dependent claims are patentable for at least similar reasons as those for the claims on which they depend are patentable.

Canceled claims, if any, have been canceled without prejudice or disclaimer.

Any circumstance in which the applicant has (a) addressed certain comments of the examiner does not mean that the applicant concedes other comments of the examiner, (b) made arguments for the patentability of some claims does not mean that there are not other good reasons for patentability of those claims and other claims, or (c) amended or canceled a claim does not mean that the applicant concedes any of the examiner's positions with respect to that claim or other claims.

Please apply $555 for the Petition for Extension of Time fee and any other charges or credits to deposit account 06-1050, referencing attorney docket 17146-0008001.

Respectfully submitted,

Date: 8/19/10

David L. Feigenbaum
Reg. No. 30,378

Fish & Richardson P.C.
225 Franklin Street
Boston, MA 02110
Telephone: (617) 542-5070
Facsimile: (877) 769-7945

22479823/22367908.doc